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Title

Hold your horses: Differences in EEG correlates of inhibition in cancelling and stopping an

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Author names and affiliations

Mario Hervault¹, Pier-Giorgio Zanone¹, Jean-Christophe Buisson², Raoul Huys¹

¹ Centre de Recherche Cerveau et Cognition – UMR 5549 CNRS – Université Toulouse 3 Paul

Sabatier

² Institut de Recherche en Informatique de Toulouse – UMR 5505 CNRS – Université Toulouse 3

Paul Sabatier

Corresponding author

Mario Hervault

Cognitive Neurology Lab, Psychological and Brain Sciences, University of Iowa

340 Iowa Ave, Iowa City, IA 52242, United states

mario-hervault@uiowa.edu

Abstract

Behavioral adaptation to changing contextual contingencies often requires the rapid inhibition of planned or ongoing actions. Inhibitory control has been mostly studied using the stop–signal paradigm, which conceptualizes action inhibition as the outcome of a race between independent GO and STOP processes. Inhibition is predominantly considered to be independent of action type, yet it is questionable whether this conceptualization can apply to stopping an ongoing action. To test the claimed generality of action inhibition, we investigated behavioral stop–signal reaction time (SSRT) and scalp electroencephalographic (EEG) activity in two inhibition contexts: Using variants of the stop–signal task, we asked participants to cancel a prepared–discrete action or to stop an ongoing–rhythmic action in reaction to a STOP signal. The behavioral analysis revealed that the discrete and rhythmic SSRTs were not correlated. The EEG analysis showed that the STOP signal evoked frontocentral activity in the time and frequency domains (Delta/Theta range) in a task–specific manner: The P3 onset latency was the best correlate of discrete SSRT whereas N2/P3 peak-to-peak amplitude was the best correlate of rhythmic SSRT. These findings do not support a conceptualization of inhibition as action– independent but rather suggest that the differential engagement of both components of the N2/P3–complex as a function of action type pertains to functionally independent inhibition subprocesses.

Keywords

action inhibition, executive control, ERP, time–frequency, motor control

Highlights

- Inhibitory control was investigated in two stop–signal tasks that differed in the type of motor response to inhibit.
- Frontocentral EEG markers of inhibition differed between cancelling a prepared– discrete action and stopping an ongoing–rhythmic action.
- STOP–signal ERP components were distinctively related to inhibition in prepared– discrete (P3 onset) and ongoing–rhythmic (N2/P3 peak-to-peak amplitude) actions.
- Inhibitory control is not a generic process; its underpinning neural subprocesses are modulated as a function of action type.

1 **1. Introduction**

2 Inhibitory control is generally conceived of as a core executive function involved in the control of 3 attention, thought, emotion, and action (Bari & Robbins, 2013; Diamond, 2013; Miyake et al., 4 2000). In particular, people are apt to cancel actions rapidly when unanticipated events or 5 contextual changes occur. Some situations call for the inhibition of prepared actions, a case 6 thoroughly studied by experiments using the stop-signal paradigm: some GO stimuli are 7 unpredictably followed by a STOP signal requiring the cancellation of the prepared response 8 (Logan & Cowan, 1984; Verbruggen et al., 2019). Other situations call for the abrupt cessation of 9 ongoing actions during execution (Alegre et al., 2008; Lofredi et al., 2021). In this regard, 10 previous experimental findings strongly suggest that the behavioral inhibition latency in the two 11 situations are unrelated (Hervault et al., 2019). Still, it is unclear whether the neural processing 12 of action inhibition relies on a single set of processes, that is, whether it is action–independent 13 or action–specific. The present study addressed this issue by investigating behavioral stopping 14 latency and scalp neural activity through EEG when participants inhibited either prepared– 15 discrete or ongoing–rhythmic actions. 16 Based on the prevalent horse–race model (Logan & Cowan, 1984; Verbruggen et al., 2019), 17 inhibition can be evaluated in stop–signal tasks as the outcome of a race between independent 18 GO and STOP processes: it fails when the GO process finishes the race before the STOP process 19 and succeeds otherwise. The grounding statistical model provides an elegant way to estimate 20 the duration of the covert action inhibition process, the stop–signal reaction time (SSRT). The 21 model remains silent, however, about the underlying neural processes. The stop–signal 22 paradigm was developed as a tool to evaluate a presumably action–independent process of 23 inhibition (Band & van Boxtel, 1999; Logan & Cowan, 1984). Logan and Cowan (1984, p. 318) 24 could have been hardly more explicit about the presumption of generality when they stated that

25 "*The model developed so far is addressed to discrete tasks with discrete responses. It would* 26 *seem to be relatively straightforward to generalize the model to continuous responses*". Yet, for 27 an ongoing–continuous action, the assumed race between the GO and STOP processes 28 underlying the stop–signal paradigm cannot apply, since the GO (action initiation) process has 29 long run to its completion at the time of the STOP Signal occurrence. This argument motivates 30 our challenging the assumption that action inhibition is generic by comparing cancelling a 31 prepared–discrete action and stopping an ongoing–rhythmic action. In addition, the 32 investigation of ongoing–rhythmic action inhibition has been conceived as crucial in establishing 33 the real–world generalizability of inhibitory control (Hannah & Aron, 2021). Studying ongoing– 34 rhythmic action inhibition also provides the opportunity to measure the SSRT without relying on 35 race–model assumptions (Lofredi et al., 2021; Morein-Zamir et al., 2006; Schultz et al., 2021). 36 Inhibitory control is indispensable in everyday life to stop either type of action. Discrete actions, 37 like grasping, are delimited by moments without movement (i.e., with zero velocity and 38 acceleration). That is, a discrete action unit refers to a movement that is preceded and followed 39 by a non-negligible period in which the position of the moving limb does not change. In contrast, 40 rhythmic actions, like walking, are continuous and periodic and lack such recognizable endpoints 41 (Hogan & Sternad, 2007). The neural structures associated with controlling discrete and 42 rhythmic actions differ considerably (Schaal et al., 2004; Spencer et al., 2003; Wiegel et al., 43 2020), due to differing timing and initiation mechanisms (Huys et al., 2008; Spencer et al., 2003). 44 Thus, various lines of evidence persuasively suggest that discrete actions require additional 45 control processes, involving supplemental brain activation as compared to rhythmic actions. 46 Therefore, since discrete and continuous movements tap into distinct neural mechanisms of 47 action control, they provides an excellent window to test whether inhibition is the action–

48 independent process that is often claimed to be (Logan & Cowan, 1984; Schall et al., 2017; 49 Verbruggen & Logan, 2009a).

50 As of yet, only few studies have investigated whether the same inhibition process underwrites 51 cancelling a prepared action or stopping an ongoing action. Morein–Zamir et al. (2004) found a 52 correlation between the inhibition latencies (SSRTs) associated with cancelling a prepared action 53 and stopping an ongoing (yet) isometric action in a rather peculiar task: Participants tracked the 54 speed of a target that rotated along an imaginary circle on the screen by varying the pressure on 55 a force sensor. Therefore, while the perceptual task was clearly continuous, there was hardly 56 any movement to inhibit at all, since there was no limb displacement or trajectory to speak of. 57 In contrast, a recent investigation showed that the SSRTs associated with cancelling a prepared– 58 discrete key–pressing action (the classic stop–signal task) and stopping an ongoing–rhythmic 59 drawing action were unrelated across participants (Hervault et al., 2019). This finding 60 contradicts the assumption that a single mechanism is involved in inhibiting prepared and 61 ongoing actions. 62 Regarding the electroencephalographic (EEG) neural activity related to action inhibition in the 63 stop–signal paradigm, event–related potential (ERP) studies have linked inhibition to 64 pronounced frontocentral negativity around 200–300 ms after the STOP–signal onset (N2), 65 followed by a distinct positive activity about 150 ms later (P3) with a frontocentral to

66 centroparietal topography (Huster et al., 2013). Suggestive of their functional relevance, the

67 amplitude and latency of both waves differ between successful and failed STOP trials (e.g.,

68 Bekker et al., 2005; Kok et al., 2004). In addition, P3 onset latency correlates strongly with SSRT

69 (e.g., Wessel & Aron, 2015). Finally, both N2 and P3 predict individual differences in inhibition

70 performances (Chikara & Ko, 2019; Vahid et al., 2018). In the frequency domain, STOP trials

71 reveal augmented power in the Delta (0–3 Hz) and Theta (4–8 Hz) frequency bands compared

72 to GO trials (e.g., Chikara et al., 2014; González–Villar et al., 2016; Lavallee et al., 2014; Wessel & 73 Aron, 2013). This difference is reliably discernible between 200 and 500 ms post stimulus 74 presentation, that is, within the time range of the N2/P3–complex (Huster et al., 2013). 75 These ERP and time–frequency patterns correlate significantly with action inhibition and proved 76 to change with the loss of inhibitory control due to various disorders (Bekker et al., 2005; 77 Kusztor et al., 2019; Lansbergen et al., 2007; Tschuemperlin et al., 2019; Van Voorhis et al., 78 2019). Whereas such correlations between inhibition performance and N2/P3 ERPs and the 79 related time-frequency patterns are robust and reproducible, similar correlations have also been 80 reported between these EEG indices and multiple other behavioral measures, thus questioning 81 their specificity in indexing inhibitory processes per se (Huster et al., 2020). Hence, EEG 82 correlates could either truly reflect a, say, "pure" inhibitory process (Hynd et al., 2020; Wessel & 83 Aron, 2015), or the processing of the conflict required to inhibit action (Enriquez-Geppert et al., 84 2010), or a contextual update of the situation requiring an sporadic action revision (Waller et al., 85 2019). Thus, studying inhibition–related EEG patterns in tasks known to differ in the engaged 86 action–control processes, as it is the case for discrete and rhythmic actions, may provide 87 additional information to a functional interpretation of these EEG correlates. 88 Apart from classical stop–signal experiments, only two studies, to our knowledge, report that 89 components of the N2/P3 complex are linked to the intentional termination of ongoing actions: 90 The P3 wave was associated with ending sustained isometric elbow contraction (Hatta et al., 91 2003), while the N2 wave was related to the reactive cessation of an ongoing drawing action 92 (Sosnik et al., 2015). In view of their presumed functional relevance, EEG correlates of inhibition 93 constitute suitable candidates to address whether inhibitory processes are involved similarly in 94 cancelling and stopping action. Indeed, EEG correlates of inhibition were modulated in 95 amplitude and latency when the inhibitory requirement is varied by using stop–signal tasks,

96 stop–change tasks, and GO/NoGO tasks (e.g., Krämer et al., 2011; Raud et al., 2020).

97 Nonetheless, these studies reported EEG modulations when cancelling one action type only,

98 again, discrete action, while there is, to our best knowledge, no study investigating modulations

99 of inhibition EEG for continuous action. Therefore, no comparison across the two action types is

100 possible in terms of neural inhibition modulations.

101 To sum up, the present study probes the assumption that action inhibition generalizes across

102 action types by using tasks involving movements associated with distinct kinematics, dynamics,

103 as well as neural control mechanisms. Therefore, we recorded EEG in participants who had

104 either to cancel a prepared–discrete action or to stop an ongoing–rhythmic action performed on

105 a digitizing tablet, while keeping the movement effector and the plane of motion the same. We

106 investigated the frontocentral N2/P3–complex and Delta/Theta band activity as neural

107 correlates of inhibitory action control.

108 **2. Materials and Methods**

109 *2.1. Participants*

110 Twenty-three participants volunteered in the experiment. For three participants, behavioral and 111 EEG artifacts warranted their exclusion from the final analysis, which was therefore restricted to 112 twenty participants (12 males; 8 females, mean age 25 ± 2.4 (SD) years). All participants were 113 healthy and had normal or corrected–to–normal vision. Participants' handedness was 114 determined using the Edinburgh handedness inventory (Bryden, 1977) and only participants 115 with a homogeneous pattern of right–hand preference were included. The study was conducted 116 according to the principles stated in the Declaration of Helsinki and the procedures were 117 approved by the local research ethics committee (ID–RCB: 2020–A03215–34). In order to be 118 able to detect a difference interpreted as large (Cohen's *d* = 0.80, Cohen, 1988; Sawilowsky, 119 2009) between discrete and rhythmic inhibition latencies, and by accepting a Type 1 risk *α* of .05 120 and a statistical power 1 – *β* of .90, the required number of participants for a repeated measures 121 t-tests was minimally estimated as 15 (using G*power software, Faul et al., 2009) .

122 *2.2. Apparatus and Stimuli*

123 Participants were seated in front of a graphic tablet (WACOM Cintiq 15X, 1280×800–pixel 124 resolution). As an initial position, they put the stylus between two vertical yellow bands (1 mm 125 wide) plotted at the center of the digitizing black screen (10 mm distant). Stimuli were green or 126 blue 50 ms flashes displayed on the whole screen. Participants were requested to react to these 127 stimuli by initiating swiping movements to the right or left direction in the discrete task and by 128 continuous ongoing swiping oscillations in the rhythmic task. Occasionally, and unexpectedly 129 (see Procedure), a red 50 ms flash followed the main stimulus, indicating the participants to stop 130 the action. The *x* and *y* coordinates of the performed motions were digitized at a sampling

131 frequency of 143 Hz as long as the stylus touched the tablet. The program controlling the tablet 132 was custom-made. A hook-and-loop fastener was used to fix the participant's forearm to the 133 table in order to restraint the movement to the wrist articulation, thereby avoiding large 134 muscular noise in the EEG signal due to an intense contraction of the biceps and deltoid 135 muscles.

136 *2.3. Procedure*

137 *2.3.1. Discrete task*

138 The discrete task (**Fig. 1**) was designed following guidelines to capture the ability to inhibit 139 actions in stop–signal tasks (Verbruggen et al., 2019). The primary task was a two–choice 140 reaction time task. When a green versus blue flash appeared, participants were instructed to 141 reach to the right versus left half–side of the tablet screen, respectively, with the stylus (green 142 and blue stickers were visible on the right and left tablet sides). On 75% of the trials (GO trials), 143 only this main stimulus was presented, and the participants had to respond to the stimulus as 144 fast and accurately as they could. On 25% of the trials (STOP trials), a red flash appeared shortly 145 after the main stimulus as a STOP signal, which indicated to the participants to cancel their 146 response (secondary task). This experiment consisted of one practice block and 30 experimental 147 blocks, each consisting of 20 trials. Each trial began when the participant positioned the stylus 148 between the two centered vertical lines, and the GO stimulus occurred after 1500 ms. The time 149 interval between GO stimuli of two subsequent trials was randomized between 3500 and 4000 150 ms. In STOP trials, the GO stimulus was followed by the STOP signal after a delay (SOA; stimulus 151 onset asynchrony). The SOA, initially set to 200 ms, was dynamically adjusted in 50 ms 152 increments to achieve a probability of responding *p(respond|signal)* of .50. When the 153 participant crossed a vertical line, the STOP trial was considered as a stop failure and the SOA

154 was shortened; when the participant kept the stylus between the two lines, the STOP trial was 155 considered successful and the SOA was prolonged. Participants were asked to focus on the 156 primary GO task requiring as fast as possible swiping movements while minimizing errors. They 157 were also instructed that in some STOP trials they would fail to cancel the response but that 158 they should not be troubled by these failures.

159 *2.3.2. Rhythmic task*

160 The apparatus of the rhythmic task was similar, but the task design differed from the discrete 161 task (**Fig. 1**). As a main task, participants were not engaged in a GO task but in a CONTINUE task. 162 They were instructed to rhythmically oscillate the stylus between the two sides of the screen at 163 a spontaneous frequency. A minimal and consistent oscillation amplitude was guaranteed by 164 imposing the constraint that the oscillations' extrema had to fall outside the two centered 165 vertical lines. The main task was to pursue the action without interruption when the green or 166 blue CONTINUE stimuli appeared. In infrequent STOP trials, a red flash signal occurred after the 167 main stimulus with a fixed SOA (see below). The participants were instructed to stop their 168 ongoing–rhythmic action as soon as the STOP signal occurred and to wait for the next stimulus 169 to restart the oscillation. The repartitioning between frequent CONTINUE trials (75%) and 170 improbable STOP trials (25%) was similar to the discrete task, as well as the inter-trial duration. 171 The task was also administered in 30 blocks of 20 trials. 172 For both tasks, the main stimulus was randomly a green or blue flash but with an equal 173 probability within blocks. Participants had to maintain contact between the stylus and the tablet 174 screen during the whole block. Participants were free to choose the rest time duration between 175 the blocks (from 20s to 120s). They completed the discrete task in a first session and the 176 rhythmic task in a second session one week later. This task order was chosen as it allowed us to

177 set the fixed SOA between CONTINUE stimulus and STOP signal in the rhythmic task as the mean 178 of the SOAs between GO stimuli and STOP signal obtained by each participant in the discrete 179 task. This procedure ensured that the average delay between the main (GO/CONTINUE) 180 stimulus and the secondary (STOP) signal were similar in both tasks, and so was the perceptual 181 neural activity.

182 *2.4. EEG recording and preprocessing*

183 Scalp–EEG signals were acquired with 64 Ag/AgCl active pin electrodes at 2048 Hz (Biosemi 184 Active Two 10/20 system). Data were referenced online with a CMS/DRL feedback loop and 185 online low–pass filtered. Electrode offsets (difference in mV of each channel from the CMS 186 electrode) were examined after electrode application, which was adjusted if the absolute value 187 exceeded 15 mV. Three additional face electrodes recorded the vertical and the horizontal 188 electrooculograms. Digital markers (event codes) were inserted into the continuous EEG via a 189 DB25 cable through a parallel port interface. Continuous EEG data were imported and 190 preprocessed in bespoke scripts using functions from the EEGLAB Matlab plugin (Delorme & 191 Makeig, 2004). Data were downsampled to 500 Hz, high–pass filtered at 0.1 Hz, and low–pass 192 filtered at 50 Hz with a linear finite impulse response filter. EEG epochs corresponding to task 193 trials were generated by extracting data from –1000 to 2000 ms around each main stimulus 194 event (GO or CONTINUE stimulus onset for the discrete and rhythmic task, respectively). After 195 epoching, the recording was visually inspected for non-stereotypical artifacts (such as muscle 196 activation or intermittent electrode artifacts) and any epoch found to contain an artifact was 197 removed from the data. EEG was finally re–referenced to the average of all channels. 198 Independent component analysis (Infomax ICA; Bell & Sejnowski, 1995) was applied to 199 continuous EEG data (concatenation of the EEG epochs) to identify neural components 200 contributing to the observed scalp data. In the original scalp 64-channel data, each row of the

201 data matrix represents voltage, summed between source projections to one data channel. After

202 decomposition (64 components), each row of the data matrix gives the time course of the

- 203 activity of one component process spatially filtered from the channel data (Delorme & Makeig,
- 204 2004). Using the ICLABEL classifier (Pion-Tonachini et al., 2019) over the 30 first components,
- 205 components identified as artifactual, i.e., with less than 5% chance to account for neural activity,
- 206 were removed from the EEG data structure, thus removing their contributions to the observed
- 207 EEG. Rejection was systematically checked by visual inspection of component properties (time
- 208 series, spectra, topography) according to ICLABEL guidelines (ibid.), leading to an average
- 209 number of 7 components rejected by participant (min = 4 ICs, max = 9 ICs). Across all
- 210 participants, these procedures led to the omission of 8.8 % of the STOP trials in the discrete task
- 211 (SD = 1.6 %) and 4.1 % of the rhythmic STOP trials (SD = 1.7 %).

212 *2.5. Behavioral measures*

213 Data analyses were performed using Matlab™ software (Mathworks 2013).

214 *2.5.1. Discrete stop task*

215 Reaction times (RTs) were computed for both action initiation and inhibition. For each GO trial, 216 GoRT was calculated as the time between the GO stimulus onset and the response onset, the 217 latter being defined as the moment the swipe had exceeded 5% of the Euclidean distance 218 between the initial and furthest (i.e*.*, end) position of the movement response. The discrete 219 stop–signal reaction time (SSRTd) was computed using the integration method with 220 replacement of GO omissions, which entails selecting the nth GoRT, where *n* equals the number 221 of RTs in the GoRT distribution multiplied by the overall *p(respond|signal)*. The SSRTd is then 222 obtained by subtracting the mean SOA from the nth GoRT (Verbruggen & Logan, 2009a) (Fig. 2). 223 The SSRTd could be estimated for all of the 20 participants as their *p(respond|signal)* did not

224 differ significantly from .50 (see Results). Fail–STOP RT was computed as the reaction time 225 measured in failed STOP trials (FsRT).

226 *2.5.2. Rhythmic stop task*

227 In each STOP trial, the SSRT (SSRTr) was computed using the methodology developed in a

228 previous study (Hervault et al., 2019). Briefly, stop time was calculated as the latency between

229 the STOP signal onset and the end of the action, identified when the motion velocity reduced to

- 230 null following the STOP signal. Within the stop time, SSRTr was calculated as the latency
- 231 between the STOP signal onset and the onset of the response adjustment (**Fig. 2**). This time
- 232 point was defined as the moment the ongoing trajectory in phase space (i.e., the space spanned
- 233 by x and dx/dt) deviated relative to movements without a STOP signal according to statistical
- 234 criteria based on a sample's position in phase space, and the angle and magnitude of its
- 235 corresponding velocity vector (Hervault et al., 2019).

236 *2.6. Scalp activity measures*

237 The neural network engaged in inhibitory control (Aron, 2007; Lofredi et al., 2021) has been 238 mainly associated to ERPs and time-frequency power visible at frontocentral sites, when 239 investigated using EEG (Chikara et al., 2014; González-Villar et al., 2016; Huster et al., 2013; 240 Lavallee et al., 2014; Wessel & Aron, 2013, 2015). According to this literature, the following 241 analyses were performed using the three FCz, Cz and CPz EEG channels. In addition, the occipital 242 Oz channel was added to the ERP analysis to evaluate the potential contribution of the attention 243 in our task comparison. Especially, the visual N1 wave reflects the operation of a discrimination 244 process within the focus of attention. Indeed, N1 appears to be larger when participants are 245 performing discrimination tasks than when they are performing detection tasks (Vogel & Luck, 246 2000).

247 *2.6.1. Event–related potentials*

248 For the main task's ERP, we averaged the EEG time series locked to the main stimulus onset (GO 249 or CONTINUE) following the subtraction of a −200 to 0 ms pre–stimulus period as baseline. As 250 STOP trials contained both the main stimulus (GO or CONTINUE) and the subsequent STOP 251 signal, the STOP–signal–locked ERP cannot be directly and reliably computed as it may be 252 contaminated by residual main–stimulus related activity (if not removed by the averaging 253 process; Woldorff, 1993). For the rhythmic task, this overlapping problem was overcome by 254 computing the neural activity difference of the main–stimulus locked ERP between STOP trials 255 and CONTINUE trials, and then re-locking the STOP trial ERP to the STOP signal onset. This 256 procedure, however, cannot be used for the discrete task, where the SOA delay (duration 257 between GO stimulus and STOP signal) was adjusted across trials. To assess differences in the 258 STOP–signal–processing irrespective of differences in the GO–stimulus processing, we 259 computed, for the discrete task, the difference EEG activity separately for successful and failed 260 STOP trials, in a similar manner as in previous studies (see Krämer et al., 2011; Ramautar et al., 261 2004, 2006). Specifically, GoRTs associated with the GO trials were rank–ordered, and then split 262 into two parts. According to the horse–race model the fast and slow tails of the GoRTs 263 distribution corresponded to the proportion of failed and successful STOP trials, respectively 264 (Verbruggen & Logan, 2009a). Thus, ERPs were averaged across slow GO trials. This "virtual" 265 GO–trials–ERP was then subtracted from successful STOP trials EEG data. STOP trials ERP was 266 then computed and re-locked to the STOP–signal–onset accounting for the SOA delay of the 267 successful STOP trials.

268 *2.6.2. Time–frequency analysis*

269 The EEG signals were convolved with complex 3 to 8–cycle–long Morlet's wavelets. Their central

270 frequencies were changed from 0.5 to 50 Hz in 0.5 Hz steps. From the wavelet transformed

271 signal, $w_k(t, f)$, of trial *k* at time *t* (2 ms time resolution) and with frequency *f*, the

272 instantaneous power spectrum $p_k(t,f) = R(w_k(t,f))^2 + I(w_k(t,f))^2$ and instantaneous

273 phase $\varphi_k(t,f) = \arctan\{I(w_k(t,f)) / R(w_k(t,f))\}$ were extracted (R and I symbolize the real

274 and imaginary parts of a complex number, respectively). Using the instantaneous power

275 spectrum, $p_k(t, f)$, the average power spectrum was computed for each participant in the GO,

276 CONTINUE, and STOP conditions as follow:

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

278 As for the ERPs computation, GO and CONTINUE Power was subtracted from its respective STOP 279 trials results (see above). Power was then normalized with respect to a −500 to -200 ms pre–

280 stimulus baseline and transformed to decibel scale $(10 \cdot \log_{10} 0)$ the signal).

281 *2.6.3. Statistical analysis*

282 To assess differences in the STOP-signal related neural activity between discrete and rhythmic 283 action stopping, we subjected the individual ERP vectors and Power matrices to a non– 284 parametric permutation procedure (Maris & Oostenveld, 2007). For this purpose, the 0 to 800 285 ms time window of the participants' STOP-signal locked ERP was used. Regarding the individuals' 286 Power matrices, we used a similar time-window associated with a 2 to 8 Hz frequency-window. 287 These windows contains both the time (N2/P3) and frequency ranges (Delta/Theta) of interest 288 to investigate inhibitory processes (Huster et al., 2013). A 0 to 300 ms window was used for the 289 occipital Oz ERP permutation testing.

290 ERPs of a given EEG channel were subjected to a non-parametric permutation procedure, at the 291 group level (Maris & Oostenveld, 2007). The 20 participants' windowed ERPs were pooled over 292 the two STOP conditions (20 by conditions). Two sets of 20 ERPs each were then drawn 293 randomly from this pool, and the differential grand-average ERP was computed between the 294 two sets. This procedure was repeated 10 000 times, thus producing a distribution of these ERPs 295 based on shuffled data under the null hypothesis. For each time point, a *p*-value was computed 296 as the proportion of these pseudo-differential ERPs that exceeded the observed participants' 297 average differential ERP. This *p*-value thus indicates at which time point the observed power 298 distribution for the two conditions is more divergent than expected for random data (*p* = .05 299 threshold). To correct for multiple comparisons, we analyzed the resulting distributions of *p*-300 values to compute *p*-thresholds corresponding to the 2.5th percentile of the smallest, and the 301 97.5th percentile of the largest *p*-values distribution (Cohen, 2014). This permutation analysis 302 was similarly applied to each time-frequency point to assess the Power matrices significance 303 between the two STOP conditions.

304 Next, brain-behavior correlations were computed. For each of the three frontocentral channel 305 ERPs, N2 peak amplitude was computed by searching for the local peak with the minimal value 306 in the 100–300 ms time range. N2 onset latency was defined as the time when half of the N2 307 peak amplitude value was reached (Lopez-Calderon & Luck, 2014). Peak amplitude and onset 308 latency were computed in the same way for the P3 wave but now by searching for the maximal 309 value in the 200–500 ms range. ERP peak and onset detection were visually checked for each 310 participant and each channel. In addition, the N2/P3 peak-to-peak amplitude was computed. 311 Each of these five measures was then subject to a Pearson correlation test with the behavioral 312 SSRT value. Resulting *p*-values were corrected using Bonferroni correction, that is, by multiplying

- 313 each *p*-value by the number of tests (i.e., five). Similarly, time-frequency Power peak amplitude
- 314 and peak latency were computed and correlated to SSRT using the same correction (two tests).

315 **3. Results**

316 *3.1.Behavior*

317 Main behavioral results are reported in **Table 1**. Importantly, FsRT (M = 424 ms, SD = 51 ms) was 318 significantly shorter than GoRT (M = 474 ms, SD = 58 ms) for each single participant (paired-t-319 tests, *p* < .01). The participants' *p(respond|signal)* (M = .53, SD = .08) was not significantly 320 different from .50 (*t(19)* = 0.33, *p* = .74, CI95[.44, .61], *Cohen's d* = 0.37) , and this probability 321 increased sigmoidally with the SOA (i.e., the inhibition function). These analyses confirm the 322 validity of the race–model between GO and STOP processes in the discrete task, validating the 323 computation of the SSRTd in accordance with the model. In the rhythmic task, the spontaneous 324 oscillation frequency was 1.60 Hz on average (SD = 0.55 Hz). Previous studies have shown that 325 movement performed at this frequency were continuously rhythmic (Hermes et al., 2012; 326 Seeber et al., 2016; Toma et al., 2002) and that the stopping latencies computed in the same 327 task was not dependent of the movement phase (Hervault et al., 2019). The participants' mean 328 Stop Time (M = 399, SD = 34 ms) and mean SSRTr (M = 268, SD = 24 ms) correlated strongly 329 (*Pearson r(18)* = .78, *p* < .001, CI95[-.52, .91]), which underlines the contribution of the inhibition 330 process in the final stopping performance. Across the 20 participants, the SSRTd (M = 268 ms, 331 SD = 52 ms) pertaining to the discrete task and the SSRTr (M = 270 ms, SD = 24 ms) pertaining to 332 the rhythmic one did not differ (paired t-test, *t(19)* = -0.08, p = .93, CI95[-23 ms, 21 ms], *d* = 0.05). 333 Crucially though, the inhibition times of both tasks were unrelated across participants (*r(18)* = - 334 .04, *p* = .86, CI95[-.47, .41], **Fig.5**). As a validity check, we next verified whether for the rhythmic 335 task the SSTRr values measured in the first 15 blocks of trials versus the second 15 blocks of 336 trials were correlated, and found a positive significant correlation (*r(18)* = .81, *p* < .001, CI95[-.56, 337 .92]). To ensure that participants did not proactively anticipate the STOP signal occurrence, we 338 tested whether the rhythmic movement was slow down at the SOA latency (Schultz et al., 2021). 339 Including all the rhythmic STOP trials of our participants, we compared the movement mean 340 velocity of the 100 ms time window surrounding the STOP signal occurrence $(-50 \text{ ms to } +50 \text{ ms})$ 341 to the movement mean velocity of the 100 ms time window surrounding the CONTINUE 342 stimulus occurrence. This comparison (paired *t*-test) failed to show a significant difference 343 between the two time windows for both the x-velocity $(t_{12709}) = -0.10$, $p = .92$) and y-velocity 344 $(t_{(2709)} = 0.47, p = .64)$, indicating that the participants did not proactively adapt their movements 345 in either movement dimension.

346 *3.2. EEG time domain*

347 The ERP analysis showed that both N2 and P3 waves were evoked in the two stop–signal tasks, 348 yet with clear differences between the discrete and rhythmic actions (**Fig. 3**). Indeed, the 349 permutation analysis identified a significantly higher voltage in the discrete STOP condition as 350 compared to the rhythmic STOP condition in the 218 - 458 ms time window at FCz, in the 204 - 351 450 ms time window at Cz and in the 202 - 254 ms time window at CPz (*p* < .05, corrected). The 352 topographies of the ERP plotted at N2 and P3 peak latency (**Fig. 3**) confirmed the frontocentral 353 locus of the evoked activity, excepted for the N2 discrete STOP condition for which the small 354 amplitude was associated to a less focused activity. In contrast, the Oz site showed a lower 355 voltage in the discrete STOP condition, as compared to the rhythmic one, which was significant 356 in the 228 - 280 ms time window. This difference was present after the early, negative, N1 wave 357 (**Fig. 3**), probably occurring later than perceptual detection of the STOP signal (Hillyard et al., 358 1998; Luck, 2014).

359 The N2 and P3 peak values and onset latencies, as well as the N2/P3 peak-to-peak value were 360 computed for each of the three frontocentral channels (FCz, Cz, CPz) and correlated to behav-361 ioral inhibition latencies. Mainly, at FCz site P3 onset latency was significantly correlated to SSRT 362 in the discrete STOP condition (*r(18)* = .69, corrected *p* < .01, CI95[.35, .87], **Fig. 5**) but not in the 363 rhythmic one (*r(18)* = .15, *p* = .52, CI95[-.31, .55]). In contrast, the N2/P3 peak-to-peak latency was 364 significantly correlated to SSRT in the rhythmic STOP condition (*r(18)* = -.57, corrected *p* = .04, 365 CI95[-.81, -.17]) but not in the discrete one (*r(18)* = -.21, *p* = .37, CI95[-.59, .25]). SSRT correlation 366 with P3 onset latency was also significant at the Cz site in the discrete STOP condition (*r(18)* = .50, 367 corrected *p* = .02, CI95[.08, .77]). No other ERP-behavior correlation was significant.

368 *3.3. EEG time–frequency domain*

369 The grand average Delta/Theta–window STOP-signal locked power maps are displayed in **Fig. 4**. 370 A clear frontocentral power increase was present in the Delta/Theta range after STOP signal 371 occurrence, with differences between discrete and rhythmic conditions. Indeed, the permuta-372 tion analysis identified a significantly higher power in the discrete STOP condition as compared 373 to the rhythmic STOP condition for time-frequency points included in a 3.5 - 6.5 Hz / 128 - 368 374 window at FCz, in a 4.5 - 7 Hz / 268 - 382 window at Cz and a 4 - 7.5 Hz / 212 - 376 window at 375 CPz (*p* < .05, corrected, **Fig. 4**). 376 The Power peak values and latencies were computed for each of the three frontocentral chan-377 nels (FCz, Cz, CPz) and correlated to behavioral inhibition latencies. Power peak latency was 378 significantly correlated to SSRT in the discrete STOP condition when computed at FCz (*r(18)* = .52, 379 corrected *p* = .04, CI95[.10, .79]) and Cz sites (*r(18)* = .60, corrected *p* = .01, CI95[.20, .83]), whereas 380 Power peak amplitude was significantly correlated to SSRT in the rhythmic STOP condition at FCz 381 (*r(18)* = -.53, corrected *p* = .04, CI95[-.79, -.09]). No other Power-behavior correlation was signifi-382 cant.

383 **4. Discussion**

384 Prior work has investigated the scalp activity evoked by the successful cancellation of a 385 prepared–discrete action (Huster et al., 2013). As inhibitory processes are supposed to 386 generalize across action types, we tested whether EEG correlates of action cancellation were 387 also observed when stopping an ongoing–rhythmic action. Comparing discrete and rhythmic 388 movements, which are fundamentally distinct in terms of their dynamics (Hogan & Sternad, 389 2007) and engage distinct brain areas (Schaal et al., 2004), proved a fruitful strategy to 390 investigate the assumption that action inhibition is an action–independent process. 391 *4.1. About unitary of action inhibition* 392 The behavioral analysis indicated that the SSRTs did not differ between the discrete and 393 rhythmic tasks and were within the range found in previous studies, including various discrete 394 responses (e.g., Boucher et al., 2007; Kok et al., 2004; Krämer et al., 2011; Montanari et al., 395 2017). Critically, the absence of a correlation between the 20 participants' inhibitory 396 performances in the discrete and rhythmic tasks, a finding consistent with previous work 397 (Hervault et al., 2019), challenges the notion that the processes inhibiting actions are 398 fundamentally task–independent. This finding is strengthened by the strong positive correlation 399 between blocks of rhythmic tasks, emphasizing that the absence of a correlation between the 400 discrete and rhythmic task does not simply reflect weak performance reproducibility. It rather 401 signifies that genuinely distinct processes, at least partly so, are implicated in the inhibition of 402 discrete and rhythmic actions. The EEG analysis corroborated this conclusion: Although the 403 STOP signals evoked a distinctive N2/P3–complex in the time domain and, concurrently, a

404 Delta/Theta power increase in the frequency domain in both tasks, these inhibition–related EEG 405 patterns differed significantly between tasks and, crucially, did so in a functionally relevant

406 manner.

407 N2 and P3 waves were both evoked in the two tasks. Strikingly though, a later P3 onset latency 408 was associated with a longer SSRT in the discrete task, but not in the rhythmic task. In contrast, 409 a larger N2/P3 peak-to-peak amplitude was associated with a shorter SSRT in the rhythmic task, 410 but not in the discrete one. For the discrete task, these findings confirm the P3 - SSRT 411 correlation previously reported, with an earlier SSRTs being associated with higher P3s (e.g., 412 Huster et al., 2014), as well as earlier P3s (Anguera & Gazzaley, 2012; Wessel, 2018; Wessel & 413 Aron, 2015); the reported correlation values were more inconsistent for the N2 – SSRT relation 414 (e.g., Anguera & Gazzaley, 2012; Raud & Huster, 2017; Senderecka, 2016). Thus, N2 and P3 may 415 act as partially dissociated correlates of inhibition processes, their importance varying as a 416 function of the type of movement to revise. Such functional partial dissociation between 417 discrete–task conditions was previously advocated by isolating the neural generators underlying 418 the occurrence of two ERP waves in a combined GO/NoGO – stop–signal task. The anterior part 419 of the mid–cingulate cortex was identified as the origin of the N2 differences between 420 conditions (GO, NoGO, STOP), whereas the inferior frontal gyrus as well as the posterior part of 421 the mid–cingulate cortex were identified as at the origin of the P3 differences (Enriquez– 422 Geppert et al., 2010; Huster et al., 2010). In another framework, an fMRI frontocentral 423 dissociation between discrete and continuous action generation has been reported in the mid– 424 cingulate area (Schaal et al., 2004). While further investigation is needed to interpret these 425 activations in the context of action inhibition, this dissociation may play a role in the differential 426 involvement of N2 and P3 waves in action inhibition. 427 Our results also indicate that time–frequency elicited by the STOP signal in the Delta/Theta

428 frequency range differed between the two tasks, this power increase being significantly related 429 to inhibitory performance in both situations. Therefore, a STOP–signal–related Delta/Theta 430 power increase can be viewed as more generically engaged in inhibitory processes. Indeed, a

431 Delta/Theta power increase has been associated with the conflictual/decisional requirement of 432 tasks in various situations (Cavanagh et al., 2012; Harmony, 2013). Our findings are thus in line 433 with the idea that action inhibition pertains to a conflict management between the regular main 434 stimulus (GO or CONTINUE) and the occasional STOP signal. Taken together, the present findings 435 demonstrate that SSRTs and related frontocentral EEG patterns differed between cancelling a 436 prepared–discrete action and stopping an ongoing–rhythmic action, suggesting that the neural 437 processes underlying inhibitory control are modulated as a function of action type.

438 *4.2. Different inhibitory subprocesses*

439 The STOP–related Delta/Theta power increase was visible in the two STOP conditions whereas

440 the N2 and P3 ERP waves were more specifically engaged in rhythmic action stopping and

441 discrete action cancelling, respectively. This dissociation between the STOP–signal evoked ERPs

442 allows for different interpretations following different conceptualizations of cognitive

443 functioning in inhibitory control.

444 First, this dissociation may indicate differences in conflict processing between the two tasks. N2 445 and P3 waves are classically observed in conflictual situations, such as action inhibition 446 (Ramautar et al., 2004), interference monitoring (Groom & Cragg, 2015), or task switching (Kopp 447 et al., 2020). In GO/NoGO and stop–signal tasks, conflict arises whenever infrequent responses 448 are required in the face of frequent responses (Braver et al., 2001; Mirabella, 2014). More 449 specifically, high conflict occurs when infrequent STOP responses have to overcome the 450 prepotency of frequent responses. In discrete inhibition tasks, previous work has shown that N2 451 indicates the occurrence of the conflict in information processing, whereas P3 relates to the 452 resolution of the conflict by inhibiting the action (Enriquez–Geppert et al., 2010; Randall & 453 Smith, 2011). Interpreting our results along this line, conflict detection might be more crucially

454 engaged in stopping an ongoing action (as reflected by a larger N2 negativity), while conflict 455 resolution would be so in cancelling a preplanned action (as reflected by a higher P3 wave). Still, 456 the overall balance between the two conflict–related subprocesses may result in similar 457 inhibition latencies, as reflected by the statistically indistinguishable SSRTs. The analysis of the 458 occipital Oz channel revealed no significant difference between the tasks regarding the early 459 visual N1 wave, suggesting that the two tasks did not differ regarding early attentional 460 processes, but did so for later cognitive control engagement. The higher P3 amplitude observed 461 in the discrete task may reflect the allocation of more resources in resolving the conflict, when 462 the GO vs. STOP response is more conflictual than the CONTINUE vs. STOP response. This 463 functional dissociation can find support in prior work requiring prepared–discrete actions 464 (Enriquez–Geppert et al., 2010; Randall & Smith, 2011). To extend its plausibility in the context 465 of ongoing–continuous actions, further investigation is needed manipulating the requirement 466 associated to the infrequent signal (i.e., STOP, CONTINUE). 467 Second, the observed EEG dissociation between discrete movement cancellation and rhythmic 468 movement stopping may reflect task–specific differences in brain predictive processing. 469 Assuming that the brain is a predictive organ, cortical responses can be seen as transient 470 expressions of prediction error (Friston, 2005). The P3 wave, which commonly follows low– 471 probability signal occurrence, would index the update of a mental representation of the 472 environment (Polich, 2007). Comparably, motor control has been modeled as a dual– 473 representation system comparing the predicted and the actual states of the effector (Synofzik et 474 al., 2008). Thus, P3 would reflect prediction error processing that is common to both 475 sensorimotor and cognitive functions. In the case of movement generation, multiple studies

476 have distinguished discrete and rhythmic continuous actions on the basis of the engaged

477 representation of time (Ivry & Spencer, 2004; Zelaznik et al., 2002). Briefly, the timing control of

478 discrete actions requires an explicit process, that is, it depends on an explicit representation of 479 the passage of time. In contrast, the timing of continuous actions is implicit as the temporal 480 properties of the action are presumably emergent (i.e., an explicit representation of time does 481 not directly guide performance). This fundamental distinction between the two action types 482 may, in the present experiment, result in distinct mental predictions accompanying the 483 processing of the GO and the CONTINUE stimuli (e.g., related to the temporal dimensions of the 484 movement, Krigolson et al., 2008). The unexpected STOP signal causes a prediction error being 485 indexed by P3 occurrence. Given that the STOP signal probability (25 %) was the same between 486 the two tasks, as was the mean SOA, the differences in P3 measures may imply a prediction 487 error modulation due to the discrete or continuous type of the action. Indeed, the explicit 488 representation of time in the discrete task is plausibly accompanied by a "strong" prediction 489 related to the movement execution. In contrast, the implicit timing processing in the rhythmic 490 task can be accompanied by a "weak" prediction. Thus, the prediction violation evoked by the 491 STOP signal might be extended in the discrete STOP trial as compared to the rhythmic STOP trial, 492 as suggested by a higher P3 amplitude in the discrete condition. To further investigate this 493 hypothesis, future EEG studies might manipulate the "prediction level" by varying the 494 probability of the STOP signal (Dimoska & Johnstone, 2008) and/or by varying the SOA between 495 the main stimulus and the STOP signal, in the two action types.

496 Third, another account on inhibitory control posits that performance in a stop–signal task 497 encompasses both "reactive inhibition" and "proactive inhibition". Thus, participants may adjust 498 the response speed to the main stimulus when anticipating the occurrence of the improbable 499 STOP signal (Verbruggen & Logan, 2009b). In the discrete task, these strategic adaptations allow 500 adjusting the preparation of the response to the GO stimulus. In the rhythmic task, such 501 adaptation appears unlikely, as there is no response preparation to adjust when the CONTINUE

502 stimulus appears while the movement is ongoing. In addition, no proactive slowing of the 503 ongoing rhythmic movement was shown in the present study. Thus, action inhibition might 504 involve both reactive and proactive processes in the discrete cancellation, whereas only reactive 505 processes would be engaged in the rhythmic stopping. The proactive process, which modifies 506 the neural implementation of inhibitory control (Kenemans, 2015; Leunissen et al., 2016), could 507 thus cause the observed differences in brain activity engaged in the two tasks. To examine this 508 tentative explanation, further EEG studies should manipulate cued–based proactive 509 engagement (Verbruggen & Logan, 2009b) or capture the proactive/reactive balance through a 510 kinematic movement analysis (Benedetti et al., 2020; Schultz et al., 2021).

511 *4.3. Implications*

512 Inhibitory control is known to rely on a fronto–basal ganglia brain network (Aron, 2011; Lofredi 513 et al., 2021). Recent studies found this network to become active when facing various 514 unexpected events, leading to a "*unified theory*" of inhibition (Wessel & Aron, 2017). Our 515 findings are incompatible with the view of action inhibition as a unitary construct but are readily 516 accommodated in a framework holding that different components of a unique fronto–basal 517 ganglia inhibition network are implicated in inhibition in an action–type dependent manner. 518 Thus, given a potential dissociation within the cingulate cortex enrollment (see also section 519 4.1.), the relative engagement of different parts of the inhibitory network may vary as a function 520 of the action type. Along this line, the fronto–basal ganglia brain network was recently shown to 521 be differentially engaged depending on the task constraints, such as facing STOP or NoGO 522 signals (Raud et al., 2020).

523 The activation of different neural subprocesses depending on action type has two important 524 implications. The first is technological. Devices such as a wheelchair, a robotic arm, or a drone

525 can be controlled through different kinds of movements via brain–computer interfaces (BCI). 526 Chikara and Ko (2019) suggested that the neural activity related to inhibition, particularly the P3 527 wave, can be used as a stop signal. However, given the assumption of dissociate processes of 528 action inhibition, cancelling a prepared–discrete response (e.g., grasping the wrong object) and 529 stopping an ongoing–continuous action (e.g., wheelchair displacement) might require dissociate 530 neural command based on P3 and N2/P3 peak-to-peak amplitude, respectively. The second is 531 methodological and clinical. While the "discrete" procedure for SSRT estimation leads classically 532 to a single across-trials SSRT per participant, ongoing–continuous actions offer a way of 533 measuring single–trial SSRTs that would not depend on an inhibition function inferred 534 statistically. This within–trial variability would be of particular interest for assessing (action) 535 inhibition in troubles such as Attention–Deficit / Hyperactivity Disorder (ADHD) (Morein–Zamir 536 et al., 2008). This disorder has been associated with longer SSRT and specific ERP signatures in 537 discrete–response cancellation tasks (Bekker et al., 2005). Nonetheless, given the temporal 538 variability characteristic of ADHD, a more variable inhibition latency might be a singular 539 characteristic of the ADHD population, rather than a longer latency (Castellanos et al., 2006; 540 Lijffijt et al., 2005). Consequently, tasks allowing for within–trial SSRT determination, such as the 541 rhythmic task used here, could be instrumental in revealing an inhibitory deficiency in ADHD.

542 *4.4. Conclusion*

543 The present article raises a key question about inhibitory control: Are the neural mechanisms 544 underlying inhibition action–independent or action–specific? We addressed this issue by 545 comparing cancelling a prepared–discrete response and stopping an ongoing–rhythmic action. 546 Behavioral analysis provided a first indication that inhibition of the two action types is controlled 547 differently. Consistent therewith, EEG analysis further revealed that the components of the 548 frontocentral N2/P3–complex are implicated in inhibition in an action–type dependent manner.

- 549 Extending our understanding of inhibition requires the identification of the task constraints that
- 550 set inhibition "types" apart versus those that do not, and to spell out principles allowing for an
- 551 unambiguous delineation of such types in neural space.

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Fig.1: **Discrete and rhythmic tasks design**

Participants responded to the main stimulus by initiating a discrete movement (in the discrete GO condition; *upper panel*) or continuing a rhythmic movement (in the rhythmic CONTINUE condition; *lower panel*). In 25 % of the trials, the main stimulus was unexpectedly followed by a STOP signal after a SOA, which was dynamically adjusted in the discrete task but fixed in the rhythmic one (see text).

Fig.2: **Stop–signal reaction time (SSRT) computation in the discrete and rhythmic tasks**

Discrete task (*upper panel*): graphic representation of the assumptions of the independent race model, indicating how the probability of responding or cancelling the response depends on the SOA, GoRT and SSRTd. Rhythmic task (*lower panel*): graphic representation of the stopping time course. The SSRTr is computed in each STOP trial by identifying the onset of the movement deviation relative to movements without a STOP signal (see text).

Fig.3: **EEG time–domain analysis of STOP trials**

Grand average STOP–signal locked ERPs in the discrete (STOP-D) and rhythmic (STOP-R) STOP conditions with associated topographies averaged across participants at FCz ERPs peak latencies. ERPs are displayed for three frontocentral (FCz, Cz, CPz) and one occipital (Oz) midline channels. In grey, the regions of significant difference (according to the nonparametric permutation analysis) between discrete (successful) and rhythmic STOP conditions (*p* < .05, corrected).

Fig.4: FCz time–frequency analysis of STOP trials

Grand averaged STOP–signal locked Power maps for the discrete and rhythmic STOP conditions. The differential Power maps thresholded after the permutation procedure (*p* < .05, corrected) are associated to different frequency (2 to 8 Hz) and time (0 to 800 ms) ranges that correspond to the time-frequency window included in the permutation statistical analysis. Red indicates significantly increased activity (two–sided *p*, upper tail) in the discrete compared to the rhythmic task.

Fig.5: Correlation analysis

Main ERP-behavior correlations reported across participants for the FCz site (see main text for statistical values). The right panel shows the non-significant correlation between SSRT values computes in the discrete and rhythmic STOP tasks.

***** $p < .05$, ****** $p < .01$ (after correction for multiple comparisons), ^{NS} $p > .05$

Tab.1: **Main Behavioral measures of the two tasks (Mean and SD values)**