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Recalibration of inhibitory control systems during walking-related dual-task interference: A Mobile Brain-Body Imaging (MOBI) Study

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ABSTRACT

Walking while simultaneously performing cognitively demanding tasks such as talking or texting are typical 21 complex behaviors in our daily routines. Little is known about neural mechanisms underlying cortical resource 22 allocation during such mobile actions, largely due to portability limitations of conventional neuroimaging tech- 23 nologies. We applied an EEG-based Mobile Brain-Body Imaging (MOBI) system that integrates high-density 24 event-related potential (ERP) recordings with simultaneously acquired foot-force sensor data to monitor gait 25 patterns and brain activity. We compared behavioral and ERP measures associated with performing a Go/NoGo 26 response-inhibition task under conditions where participants (N = 18) sat in a stationary way, walked deliber- 27 ately or walked briskly. This allowed for assessment of effects of increasing dual-task load (i.e. walking speed) on 28 neural indices of inhibitory control. Stride time and variability were also measured during inhibitory task perfor- 29 mance and compared to stride parameters without task performance, thereby assessing reciprocal dual-task ef- 30 fects on gait parameters. There were no task performance differences between sitting and either walking 31 condition, indicating that participants could perform both tasks simultaneously without suffering dual-task 32 costs. However, participants took longer strides under dual-task load, likely indicating an adaptive mechanism 33 to reduce inter-task competition for cortical resources. We found robust differences in amplitude, latency and to- 34 pography of ERP components (N2 and P3) associated with inhibitory control between the sitting and walking 35 conditions. Considering that participants showed no dual-task performance costs, we suggest that observed neu- 36 ral alterations under increasing task-load represent adaptive recalibration of the inhibitory network towards a 37 more controlled and effortful processing mode, thereby optimizing performance under dual-task situations. 38 © 2014 Elsevier Inc. All rights reserved.

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44 Introduction

Humans continuously process sensory and cognitive events while engaged in everyday activities such as walking. For example, we successfully navigate the aisles of a shopping center as we rehearse a

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shopping list and contemplate the necessary ingredients for that 48 evening's dinner. Most everyday situations require this type of multi- 49 tasking and brain processes have evolved to handle concurrent process- 50 ing of cognitive and motor functions. However, research on multitask 51 performance has provided clear evidence for costs, indicating that 52 cognitive-motor interference (CMI) can compromise performance 53 in one or both domains (Al-Yahya et al., 2011; Woollacott and 54 Shumway-Cook, 2002). This is particularly the case for older individuals 55 (Al-Yahya et al., 2011) where performing cognitively demanding tasks 56 while walking greatly increases the risk of falling. As such, revealing 57 the neural bases of CMI has important clinical implications and the de- 58 velopment of objective brain measures of increased cognitive-motor in- 59 terference could well provide biomarkers that predict increased risk of 60 falls, allowing for early detection and intervention. In turn, these mea- 61 sures may serve as early risk indicators (i.e. endophenotypes) for 62 those who will go on to develop clinically significant cognitive impair- 63 ments such as Alzheimer's disease. 64

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Behavioral dual-task studies have provided robust evidence for a 65 66 mutual influence suggesting that motor and cognitive functions are supported in part by common neural processes (Woollacott and 67 68 Shumway-Cook, 2002). Postural stability during walking varies depending on the complexity of the cognitive task (Woollacott and Shumway-69 Cook, 2002) and strong associations between age and speed reduction 70 71under dual-task conditions have been reported (Al-Yahya et al., 2011). 72At the same time, walking impinges on cognitive performance with 73studies showing impaired spatial memory capacity, and target detection 74time (Lajoie et al., 1993). More specifically, Lajoie and colleagues 75showed that detection time increased during the single-support phase (i.e. one foot in swing) of the gait cycle, suggesting that attentional de-76mands co-vary with differences in balance requirements during the 7778 gait cycle (Lajoie et al., 1993).

While behavioral evidence suggests reliance on common brain pro-79 cesses, only a few studies have directly assessed cortical involvement 80 during walking with (Doi et al., 2012; Holtzer et al., 2011; Uehara 81 et al., 2011) and without (Gramann et al., 2011; Gwin et al., 2011; 82 Harada et al., 2009; Kurz et al., 2012; Suzuki et al., 2008) engagement 83 in a secondary task. Studies using functional magnetic resonance imag-84 ing (fMRI) have identified relevant cortical regions, showing activations 85 during preparation and execution of rhythmic foot and leg movements 86 87 in frontal and primary motor cortex (Heuninckx et al., 2005, 2008; Sahyoun et al., 2004). Obviously these studies are limited by the lack 88 of realistic mobility of the participants. Studies using functional near-89 infrared spectroscopy (fNIRS) assessing oxygenated hemoglobin 90 (oxyHb) have reported increased oxyHb levels in the prefrontal and 9192premotor cortices of participants who were preparing to walk (Suzuki 93 et al., 2008), and that inter-individual variations in stride-time interval 94correlated positively with oxyHb response within the pre-central 95gyrus and supplementary motor area (Kurz et al., 2012). In a dual-task study by Holtzer and colleagues, oxyHb levels in prefrontal cortical 96 97 (PFC) regions increased during a "walking and talking" dual-task scenario in contrast to a walking-alone condition, especially in young par-98 ticipants. An association between trunk stability under dual-task 99 conditions and gray matter atrophy has been established (Doi et al., 100 101 2012), and a transcranial magnetic stimulation (TMS) study showed 102 that the excitability of the primary motor cortex during a dual motor task varied as a function of gait speed (Uehara et al., 2011). 103

Neuroimaging studies have been successful in defining relevant cor-104 tical areas and related changes in activity under dual-task conditions 105 106 (Holtzer et al., 2011). However, hemodynamic imaging methods lack the temporal resolution necessary to determine and dissociate the sus-107 ceptibility of specific processing stages to CMI. Broader susceptibility 108 109 with interference that affects multiple processing levels of the secondary task might be related to increased dual-task costs. Event-related poten-110 111 tials (ERP) provide temporally precise measures of information processing that are very well-suited to dissociate between sensory-perceptual, 112 cognitive and motor processing stages. Work by our group (De Sanctis 113 et al., 2012a; Nolan et al., 2009, 2011, 2012) and others (Bulea et al., 05 2013; Duvinage et al., 2013; Gramann et al., 2010, 2011; Gwin et al., 115116 2010, 2011; Gwin et al., 2011) has demonstrated the feasibility of ac-117 quiring high-density EEG to investigate evoked potentials related to perceptual and cognitive processes during active and passive self-motion. 118For example, participants standing or walking on a treadmill while 119performing a visual oddball task produced entirely typical ERP compo-120121 nents with excellent signal-to-noise characteristics (Gramann et al., 2010). 122

Here, we deployed high-density scalp EEG recordings while partici-123 pants performed a taxing visual Go/NoGo response inhibition task, 124which requires subjects to overcome a potent response tendency 125established by frequent Go stimuli to successfully inhibit response exe-126cution to NoGo stimuli. We also used force sensors attached to the sole 127of each foot to measure duration and variability of the gait cycle while 128participants walked on a treadmill (Fig. 1). To assess the influence 06 130 of walking load on response inhibition, we compared participants'



Fig. 1. Illustration of a participant walking on the treadmill wearing an EEG cap and foot pressure force sensors while performing the Go/NoGo-task.

Go/NoGo task performance under three activity conditions: 1) sitting, 131 2) walking deliberately (2.4 km/h) and 3) walking briskly (5.0 km/h). 132 We predicted that walking, particularly at higher speed, would compro-133 mise inhibitory control abilities. To assess the influence of response inhibition load on gait, we compared duration and variability of the gait cycle while participants walked on the treadmill with and without performance of the Go/NoGo inhibition task. 137

EEG based studies identifying specific phases of inhibitory network 138 activity have distinguished relatively early automatic processes, as 139 represented by the N2 component (250-350 ms), from late controlled 140 processes, as represented by the P3 component (400-550 ms) (Eimer, 141 1993; Falkenstein et al., 1995, 1999). We set out to investigate 142 walking-related effects on the N2 and P3 components, allowing us to as- 143 sess the susceptibility of different inhibitory processing stages to CMI. 144 Furthermore, effects of CMI at the sensory-perceptual processing level 145 were assessed by considering the visual-evoked potential (VEP) to the 146 NoGo stimulus. Based on preliminary results by our group (De Sanctis 147 et al., 2012a), which showed that CMI strongly modulated the N2 com- 148 ponent, we predicted increased susceptibility of early and automatic 149 processing stages of inhibitory control to motor load. Furthermore, we 150 predicted an increase in stride-to-stride variability while participants 151 perform the inhibitory task, indicative of dual-task costs in the form of 152 less stable gait patterns. 153

Methods

Participants

Eighteen neurologically healthy participants (10 male) with normal 156 or corrected-to-normal vision participated in this experiment. The age 157 range was 21.8 to 36.1 years (mean 27.2 years). Written informed consent was obtained from all participants according to a protocol approved by the institutional review board at The Albert Einstein College 160 of Medicine. Participants were paid a modest fee of \$12 per hour for participating in the study. All procedures employed were compliant with 162

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163 the tenets laid out in the Declaration of Helsinki for the responsible con-164 duct of research.

165 Stimuli and task

We used 168 pictures from the International Affective Picture Sys-166 tem (IAPS), a set of normative photographs that includes content across 167168 a wide range of semantic categories (Lang et al., 2008). Only affectively neutral images were employed here and these were presented centrally 169170for 600 ms with a random stimulus-onset-asynchrony (SOA) ranging 171from 800 to 1000 ms. On average, images subtended 28° horizontally by 28° vertically. Stimuli were presented using Presentation software 172173version 14.4 (Neurobehavioral Systems, Albany, CA, USA). Participants performed a Go/NoGo task, responding quickly and accurately to 174 every presentation of an image by clicking a computer mouse button, 175 while withholding responses to the second instance of any stimulus re-176 peated twice in a row. The probability of Go and NoGo trials was 0.85 177 and 0.15, respectively. Our choice of a Go/NoGo task as the cognitive 178 challenge here was based on repeated findings that executive function-179ing, more than memory or verbal IQ, shares a common neural substrate 180 with motor processing (Holtzer et al., 2006, 2012). Versions of this sim-181 182 ple task have been widely employed in prior work (Garavan et al., 2002; Kelly et al., 2004), leading to entirely typical N2/P3 activation patterns 183 (De Sanctis et al., 2012a; Morie et al., 2013) as well as hemodynamic ac-184 tivation within areas of the neural circuit typically associated with in-185hibitory control (Bell et al., 2013). The task also leads to relatively high 186 187 rates of commission errors (i.e. erroneous button pushes to stimulus repeats) and is therefore very well-suited for the examination of the cen-188 tral hypotheses of the current study. 189

Data were acquired in five conditions: participants were asked to 190191 (1) sit and perform the response inhibition task, (2) walk deliberately 192(2.4 km/h) and perform the response inhibition task, (3) walk briskly 193(5 km/h) and perform the response inhibition task, (4) walk deliberately without performing the response inhibition task, or (5) walk briskly 194without performing the response inhibition task. Participants walked 195on a treadmill (LifeFitness TR-9000) approximately 1.5 m from a black 196 197 wall, onto which stimulus images were projected (InFocus XS1 DLP, 1400×1050 pxl). Participants completed 17 blocks (approximately 198 4 min apiece), consisting of a minimum of 4 blocks for each of the first 199 3 conditions. In addition, participants were asked to complete 2 blocks 200201 of walk deliberately and briskly without performing the cognitive task. Conditions were presented in a pseudorandom order. Subjects rested 202 between blocks to prevent fatigue. Total testing time was between 75 203and 105 min. 204

205 Gait cycle recording and analysis

To quantify the gait cycle, we attached force sensors (Tekscan 206 FlexiForce A201 transducers) to the sole of each foot. We placed trans-207208ducers at the center of the back side of the heel, the big toe ball and mid-209way along the outer longitudinal arch to detect changes in pressure force during different stance phases, including loading response, mid-210211stance, terminal stance, and pre-swing. The force signal was sampled 212 at 512 Hz using an Analog Input Box (BioSemi), which was connected 213via optical fiber with the Biosemi ActiveTwo EEG system. The continuous data were butterworth low-pass filtered at 7 Hz. Continuous data 214 were epoched at 10 s, and normalized against the standard deviation. 215 To assess stride time, we measured peak-to-peak interval using the 216 force signal derived from the right heel sensor (e.g. time of a complete 217 cycle - heel contact to next heel contact). We used automatic peak de-218 tection software (MATLAB custom scripts) with one standard deviation 219as threshold to determine if each peak was significantly larger than the 220data around it. Peak-to-peak intervals (PPI) were excluded from the gait 221222 analysis if duration to complete a cycle was < 500 or > 1500 ms.

Event related potential recording and analysis

Brain activity was recorded using a 72-channel EEG system (Biosemi 224 ActiveTwo EEG system). The data were recorded at 512 Hz and 225 bandpass filtered from 0.05 to 100 Hz (24 dB/octave). EEG data were 226 re-referenced offline to an average reference. The data were analyzed 227 offline using FieldTrip toolbox (Oostenveld et al., 2011) (see http:// 07 www.ru.nl/neuroimaging/ fieldtrip) and custom scripts for MATLAB 229 (MathWorks, Natick, MA). The continuous data were bandpass filtered 230 offline from 0.5–30 Hz (12 dB/octave). We applied an automatic artifact 231 rejection criterion of \pm 100 μ V across all electrodes in the array. Trials 232 with more than six artifact channels were rejected. On trials with less 233 than six such channels, we interpolated any remaining bad channels 234 using a nearest neighbor spline. Epochs of 1050 ms, including a 50 ms 235 pre-stimulus baseline, were analyzed. Go trials on which the partici- 236 pants responded successfully were defined as hits. NoGo trials on 237 which participants correctly withheld their response were defined as 238 Correct Rejects (CR), Trials on which participants responded incorrectly 239 were excluded from the analysis. 240

VEP amplitudes on NoGo-trials were computed using three electrode 241 sites O1, Oz, and O2 over the occipital scalp region in a time window 242 from 140 to 160 ms. Walking-related differences in VEP latency and 243 mean amplitude were assessed using two-way repeated-measures 244 ANOVA with factors of condition (sitting/walking deliberately/walking 245 briskly) and electrode site (O1/Oz/O2). 246

The N2 and P3 components on NoGo-trials were computed using 247 three electrode sites: FCz, Cz, and CPz. Electrode sites FCz, Cz, and CPz 248 were chosen based on previous studies by us and others indicating 249 that NoGo N2/P3 amplitudes are generally maximal over front-central 250 scalp regions (Eimer, 1993; Katz et al., 2010). We averaged across 251 conditions and used the grand mean ERP peak latency to encapsulate 252 a 100 ms time window for the N2 (peak latency $N2_{CR-trials} = 260$ ms, 253 N2-diff_{CR minus Hit} = 290 ms) and a 250 ms time window for the P3 $_{254}$ $(P3_{CR-trials} = 475 \text{ ms}; P3_{CR \text{ minus Hit}} = 475 \text{ ms})$ to compute the mean 255 amplitude across the respective time windows. Walking-related differ- 256 ences in N2/P3 latency and mean amplitude were assessed using two- 257 way repeated-measures ANOVA with factors of condition (sitting/ 258 walking deliberately/walking briskly) and electrode site (FCz/Cz/CPz). 259 The latency on NoGo-trials was guantified using automatic peak- 260 picking procedure (MATLAB custom scripts) which identified the 261 maximal deflection within the latency period 210-310 for the N2 and 262 350-600 ms for the P3 component. 263

Statistical cluster plot

To provide a more general description of the spatio-temporal prop- 265 erties of dual-task ERP differences, we computed statistical cluster 266 plots (SCP) for the CR_{ERP} between sitting versus walking deliberately, 267 sitting versus walking briskly and walking deliberately versus walking 268 briskly. This procedure has been used effectively in post hoc analyses 269 as a means to more fully explore complex datasets and generate pointed 270 follow-up hypotheses (Molholm et al., 2002; Murray et al., 2002). Point- 271 wise two-tailed t-tests between a given pair of conditions were calculat- 272 ed at each time-point for all electrodes. The results of the point-wise 273 t-tests from 64 electrodes are displayed as an intensity plot to efficiently 274 summarize and facilitate the identification of the onset and general to- 275 pographic distribution of walking-related modulation in ERP activity. 276 The x-, y-, and z-axes, respectively, represent time, electrode location, 277 and the *t*-test result (indicated by a color value) at each data point. 278 For each scalp electrode, only the first time point where the *t*-test 279 exceeded the 0.05 p-value criterion for at least 11 consecutive data 280 points (>20 ms at a 512 Hz digitization rate) is considered significant 281 (Foxe and Simpson, 2002; Guthrie and Buchwald, 1991). The resulting 282 statistical cluster plots are a suitable alternative to Bonferroni correction 283 for multiple comparisons, which would increase the likelihood of type II 284 errors through overcompensation for type I errors (Snyder et al., 2012). 285

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286 Topographical statistics (TANOVA)

To test for dual-task walking-related modulations in topography, we 287 288calculated the global dissimilarity (GD) (Lehmann and Skrandies, 1980) of the CR_{FRP} between sitting versus walking deliberately, sitting versus 289walking briskly and walking deliberately versus walking briskly. GD 290is a method to assess configuration differences between two scalp 291distributions, independent of their strength, as the data are normalized 292293using the global field power. The GD equals the square root of the mean 294 of the squared differences between the potentials measured at each of the 64-scalp electrodes. For each subject and time point, the GD indexes 295a single value, which varies between 0 and 2 (0 = homogeneity, 2 =296inversion of topography). To create an empirical probability distribution 297against which the GD can be tested for statistical significance, the Monte 298Carlo MANOVA was applied. This is a nonparametric bootstrapping 299 procedure, wherein each subject's data from each time point was 300 permutated such that they could "belong" to either condition. The dis-301 302 similarity was then calculated for each of 5000 such permutations for each time (Manly, 1997). 303

304 Topographical voltage maps

305 Scalp topographic maps represent interpolated voltage distributions, derived from 64-scalp measurements. These interpolated poten-306 tial maps are displayed on the 3D reconstruction of a rendered scalp 307 surface (derived from an anatomical MRI) as implemented in the 308 309 BESA2000 (Ver. 5.0) multimodal neuroimaging analysis software pack-310 age (MEGIS Software GmbH, Munich, Germany). The topographical mapping focused on the time period between 400 and 550 ms, during 311 which TANOVA revealed most robust topographical differences be-312 tween sitting and walking. 313

314 Signal-to-noise statistics

To test the signal to noise ratio (SNR) across the three conditions, we 315 computed global field power (GFP) for hits and CR evoked potentials. 316 The background noise was estimated from the pre-stimulus period 317 -100 to -40), and the signal was estimated from the first major 318 peak (100-160 ms). The squared signal was divided by squared noise 319 320 and converted to decibels in order to be scale-invariant. The resulting SNRs were subjected to 3 (condition: sitting, walking-deliberately, 321 322 walking briskly) \times 2 (trial: hits vs CR) repeated measures ANOVA. To confirm that there was minimal contamination of the broadband 323 324 evoked response from muscles and eye movements which are com-325monly shown in frequencies of 8 Hz or higher, we performed a Fast 326 Fourier Transform on the epoched Go trials for each participant and 327 computed the correlation coefficient matrix between conditions.

328 Results

329 Behavioral results

330Table 1 shows reaction times (RT), hits and correct rejection (CR)331rates for performing the Go/NoGo task during sitting, walking deliber-332ately and walking briskly. Hit rates were higher for sitting compared

t1.1 Table 1
t1.2 Reaction time (RT) and percent hits on Go trial and correct withholds on NoGo trials as
t1.3 participants performing the Go/NoGo task were sitting, walking deliberately, and
t1.4 walking briskly. Standard errors are in parentheses.

	Sitting	Walking deliberately	Walking briskly	
RT in ms	364.6 (6.2)	375.4 (8.2)	369.4 (8.1)	
Hit in %	99.7 (0.1)	99.5 (0.2)	99.5 (0.2)	
CR in %	65.2 (3.3)	66.2 (3.2)	65.8 (3.3)	



Fig. 2. Average stride time and variability (STD) in milliseconds for walking deliberately and briskly with and without engaging in a Go/NoGo inhibitory control task.

to walking (hit: $f_{2,34} = 8.8$, p = .001), although this amounted to an 333 extremely modest 0.2% performance difference in real terms. RT and 334 CR rates did not differ between sitting and either walking speeds 335 (RT: $f_{2,34} = 1.9$, p = .16; CR: $f_{2,34} = .73$, p = .48). 336

Gait analysis results

Data in Fig. 2 show the influence of performing an inhibitory task on 338 stride time and variability for seventeen¹ participants walking deliber-339 ately and briskly on the treadmill. Stride time increased while 340 performing the inhibition task ($f_{1,16} = 9.95$, p < .006), indicating that 341 participants increased stride length under dual-task load. Stride time 342 decreased while walking briskly ($f_{1,16} = 18.5$, p < .001), indicating 343 that participants required to walk faster decreased the time taken per 344 stride. No effects of dual-task and walking speed on stride-to-stride var-345 iability were observed.

Electrophysiological results

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Feasibility of recording

To illustrate the feasibility of recording ERPs with high SNR while 349 participants walk on a treadmill, we compared the SNR for the hit and 350 CR trials across all three conditions (see Table 2). The two way 351 repeated-measures ANOVA with factors of condition (sitting/walking- 352 deliberately/walking-briskly) and trial (hits/CR) revealed a main effect 353 of trial ($f_{1,17} = 63.7$, p < .0001). The effect simply results from the differ- 354 ences in the probability of Go and NoGo trials. No other effects reached 355 significance. All SNRs were extremely robust, pointing to the high 356

¹ Gait data from one participant were not obtained.

t2.1 Table 2

t2.2 Mean and standard error signal-to-noise ratio (SNR) for hit and correct reject trials duringsitting, walking deliberately, and walking briskly.

t2.4		Sitting	Walking deliberately	Walking briskly
t2.5	SNR Hit	33.9 (2.3)	37.1 (2.01)	34.9 (1.8)
t2.6	SNR CR	23.4 (2.2)	25.5 (2.2)	26.3 (1.6)

357sensitivity of the measures. These results concord with our previous 358 findings where we showed no difference between sitting and walking 359conditions for the grand mean ERP and frequency spectrum (De Sanctis et al., 2012a). In addition, we compared the frequency spectra 360 between sitting and walking using Fast Fourier Transform on the re-361362 sponses to the hit trials. The left panel of Fig. 3 shows the grand mean and standard deviation with largely overlapping spectra between con-363 ditions. The correlation coefficient values between conditions seen in 364 the right panel of Fig. 3 were all > 0.95. 365

366 ERP results

Fig. 4 shows the waveforms of the VEP for CR trials at three occipital 367 electrode sites while participants were sitting (black), walking deliber-368 ately (cyan) and walking briskly (red). Largely overlapping waveforms 369 370 across all three electrode sites were observed. Statistical assessment of 371the first positive peak amplitude within the time period from 140 to 160 ms using a two-way repeated-measures ANOVA with factors of 372 condition (sitting/walking-deliberately/walking-briskly) and electrode 373 location (01/0z/02) revealed a significant main effect of electrode loca-374375tion ($f_{2,34} = 3.8$, p < 0.031) reflecting enhanced amplitude over the left 376 occipital scalp region. No further comparisons were significant.

Fig. 5 and Table 3 show the N2/P3 component complex at three 08 378 midline electrode locations (FCz, Cz, and CPz – average reference) for 379hits (thin lines) and correct rejections (thick lines) for sitting, walking 380 deliberately, and walking briskly as well as the difference waves (CR_{ERP} minus Hit_{ERP}; right column). As can be seen most clearly in the 381 difference waves, a robust reduction in N2 amplitude was evident for 382 both walking deliberately and briskly, compared to sitting. No differ-383 ences in N2 peak latency were observed. During the P3 time period, am-384 385 plitude reduction over centro-parietal region (i.e. CPz) was observed for walking deliberately and briskly, with the strongest decrease seen for 386 walking briskly. In contrast, P3 amplitude increased over fronto-387 central regions (i.e. FCz/Cz) for walking briskly, compared to sitting. 388

The two-way repeated-measures ANOVA with factors of condition (sitting/walking-deliberately/walking-briskly) and electrode location (FCz, Cz, CPz) assessing N2 amplitude in correct rejection trials revealed a significant main effect of condition ($f_{2,34} = 15.47$, p < 0.001), electrode ($f_{2,34} = 5.8$, p = 0.006), and no condition by electrode interaction (p = 0.48). Post hoc analysis confirmed that N2 reduction was 394 reduced for walking at either speeds compared to sitting (p-values: 395 0.01 to 0.0001). The ANOVA assessing N2 difference waveforms revealed main effects for condition ($f_{2,34} = 8.41$, p < 0.001) and electrode 397 ($f_{2,34} = 49.5$, p < 0.0001), and no condition by electrode interaction 398 (p = 0.52). Post hoc analysis confirmed N2 reduction for walking compared to sitting (p-values: 0.047 to 0.005).

The two-way repeated-measures ANOVA assessing P3 amplitude in 401 correct rejection trials revealed a significant condition by electrode in-402 teraction ($f_{4,68} = 6.7$, p < 0.0001). Post hoc analysis confirmed that P3 403 reduction for walking at either speeds relative to sitting was reduced 404 only over central and centro-parietal scalp (p-values: 0.01 to 0.001). 405 No difference was observed between walking deliberately and walking 406 briskly (p > 0.15). The ANOVA assessing P3 difference waveforms re-407 vealed a significant effect of electrode ($f_{2,34} = 20.49$, p < 0.0001) and 408 a condition by electrode interaction ($f_{4,68} = 2.7$, p = 0.035). Post hoc 409 analysis did not reveal P3 differences between sitting and either walk-410 ing speeds at any of the electrode sites (0.14 < p's < 0.71).

For the P3 peak latency, a significant effect of condition ($f_{2,34} = 6.01$, 412 p = 0.006) and electrode ($f_{2,34} = 3.97$, p = 0.028) was observed. Post 413 hoc analysis confirmed that the P3 peaked earlier over centro-parietal 414 regions for walking briskly ($t_{17} = -2.4$, p < 0.027) and over fronto- 415 central regions for walking deliberately ($t_{17} = -2.8$, p = 0.012) com- 416 pared to sitting. No difference was observed between walking deliber- 417 ately and walking briskly (p = .17).

Fig. 6a shows statistical cluster plots of differential activation in CR 419 trials between sitting versus walking deliberately, sitting versus walking 420 briskly and walking deliberately versus walking briskly. The results 421 show robust clusters of differential activation between sitting and either 422 walking speeds during the N2 and P3 latency period extending across 423 fronto-parietal scalp regions. In contrast, no differential activation was 424 observed between walking deliberately and walking briskly. Fig. 6b presents the results of the TANOVAs assessing the dissimilarity of the topographic distribution between conditions across the 900-ms epoch. 427 Topographical differences between sitting and both walking speeds 428 were most robustly seen during the P3 latency period, while no difference was found for the comparison walking deliberately versus walking 430 briskly.

Fig. 7 shows the scalp topographic maps during the P3 time period on 432 correct rejection trials for sitting, walking deliberately and walking brisk-433 ly. We singled out the P3 time period for topographic mapping based on 434 TANOVA results indicating significant topographical differences during 435 this timeframe, pointing to shifts in the underlying generator configuration. During sitting, as participants performed the Go/NoGo task under 437



Fig. 3. Left panel: grand mean and standard deviation spectra of participant's visual evoked potential over central scalp regions for Hit trials during sitting, walking deliberately and walking briskly. Right panel: box plot of Pearson's correlation coefficient of the spectra between walking deliberately vs. walking briskly, sitting vs. walking deliberately, and sitting vs. walking briskly.

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Fig. 4. Grand mean (n = 18) visual-evoked potentials (VEPs) over occipital scalp regions for Hit trials during sitting, walking deliberately, and walking briskly.

single-task load, P3 maps reveal the often replicated distribution with a
maximum over central scalp (Polich, 2007). In contrast, during walking,
as participants performed the Go/NoGo task under dual-task load, maps
reveal a more anterior P3 distribution with a maximum over frontocentral scalp.

443 Discussion

Dual-task designs, particularly when used in combination with
EEG methods, have mostly deployed what could be described as a
minimalistic behavioral approach, reducing behavior in response to
task relevant stimuli to simple button presses (De Sanctis et al.,
2012b). This minimalist approach allows for precise recording of
stimulus- and response-evoked EEG activity and helps to limit the

problems of separating neural from muscle-related activity, issues that 450 can arise when participants engage in more complex real-world behav-451 iors such as walking. However, and perhaps somewhat surprisingly, we found that walking-related muscle artifacts did not substantially com-453 promise the recording of inhibition-related ERP components, and no differences in signal-to-noise ratio (SNR) and frequency spectra were 455 evident in the ERPs recorded during sitting versus walking. Indeed, 456 the standard signal-averaging approach appeared to be perfectly efficient in removing any walking-related artifacts, since the temporal dynamics of both the cognitive and walking tasks were unrelated to each 459 other (see (Gwin et al., 2010, 2011) for an alternative approach). Here we built upon recent work demonstrating the feasibility of recording high quality task-related EEG activity while participants are asked to walk on a treadmill (Gramann et al., 2010; Gwin et al., 2010, 2011; 463



Fig. 5. Grand mean ERPs for hits (left column) and correct rejections (middle column) as participants were sitting, walking deliberately, or walking briskly and performing the Go/NoGo task. The ERPs are shown at three midline electrode sites over frontal, central, and parietal scalp regions. Difference waves (ERP_{Hits} minus ERP_{CR}) are displayed in the right column.

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t3.3		Sitting			Walking deliberately			Walking briskly		
t3.4		FCz	Cz	CPz	FCz	Cz	CPz	Fz	FCz	CPz
t3.5	Ampl.									
t3.6	N2	-2.8(2.3)	-3.8(2.3)	-2.3(2.1)	-1.1(2.3)	-2.1(2.1)	-1.1(1.5)	-1.1(2.2)	-1.5(2.9)	-0.9(1.8)
t3.7	N2 diff	1.7 (2.1)	-0.3(2.3)	-1.3(2.2)	2.8 (1.7)	0.9 (1.5)	-0.1(1.1)	2.8 (2.1)	1.3 (1.8)	0.1 (1.6)
t3.8	P3	0.5 (3.0)	1.3 (2.6)	2.3 (2.1)	0.8 (3.2)	0.3 (2.9)	1.1 (1.9)	1.1 (3.3)	1.1 (3.4)	1.1 (1.9)
t3.9	P3 diff	3.7 (2.6)	3.2 (2.1)	2.5 (1.7)	4.1 (2.4)	3.1 (2.3)	2.2 (1.5)	4.3 (2.6)	3.7 (2.2)	1.9 (1.5)
t3.10 t3.11	Latency									
t3.12	N2	222 (13.2)	222 (12.2)	219 (8.6)	220 (8.8)	221 (9.2)	222 (9.3)	219 (8.3)	223 (9.3)	221 (11.1)
t3.13	N2 diff	277 (48.8)	278 (40.2)	278 (43.7)	273 (44.1)	284 (39.3)	269 (42.0)	292 (44.9)	284 (41.6)	293 (44.6)
t3.14	P3	423 (46.1)	406 (47.2)	401 (40.4)	449 (62.5)	416 (49.9)	419 (41.5)	438 (45.6)	421 (50.1)	428 (51.8)
t3.15	P3 diff	423 (49.1)	413 (46.6)	414 (53.1)	442 (47.3)	430 (43.7)	422 (50.5)	469 (49.6)	441 (47.7)	435 (44.5)

Table 3

t3.1

Makeig et al., 2009). We compared behavioral and ERP measures asso-464 ciated with an inhibitory control task under conditions where partici-465pants were sitting, walking deliberately or walking briskly, to assess 466 effects of increasingly higher dual-task load (i.e. walking speed) on 467 the neuro-circuitry supporting sensory-perceptual and inhibitory pro-468 cessing. We also compared stride timing and variability between walk-469 470 ing with and without performance of an inhibitory control task, to assess effects of dual-task load on gait parameters. 471

There were no differences in task performance between sitting and 472 either walking speeds, suggesting that participants were perfectly well 473able to perform the inhibition task while walking without suffering be-474 475havioral costs. With regard to the gait results, we found no differences in 476stride-to-stride variability, which according to numerous dual-task 477 studies has been found to increase under increasing load (Al-Yahya 478 et al., 2011). However, significant differences in stride timing were ob-479served, with an average increase in inter-stride timing of 44 ms under 480 dual-task load. As walking pace was predetermined by the speed of the treadmill, it follows that participants increased their stride length, 481 thereby making fewer, longer steps, while performing the response in-482 hibition task. Considering that the center of gravity lies almost constant-483 ly outside the base of support during walking (except for during the 484 485 relatively short phase of double-limb support), making longer steps should be associated with increased balance requirements. Previous 486 work has suggested that longer steps are more challenging because 487 the center of gravity is further from the moving base of support (Bhatt 488 489 et al., 2005), and longer steps have been linked to higher slip probability (Mover et al., 2006). On initial evaluation then, the current results seem 490 rather counterintuitive. If one assumes that participants operate under 491

limited resources, devoted and shared across both the walking and re- 492 sponse inhibition task, making longer steps might appear a less efficient 493 strategy. How then do the current results relate to the extant literature 494 on walking-related dual-task costs? 495

Some studies found an increase of stride variability and a decrease in 496 cognitive performance (Beauchet et al., 2005; Szturm et al., 2013) while 497 others reported no differences under dual-task load (Li et al., 2012). In 498 line with our results are findings by Loevden and colleagues (Lovden 499 et al., 2008), who showed no differences in cognitive performance and 500 an increase in stride time under dual-task load. These rather mixed re- 501 sults might be taken as indications that under certain circumstances 502 young walkers are able to flexibly adapt performance so that costs in 503 one or both tasks are prevented. With regard to our results, one could 504 make the argument that the number of times one executes the walking 505 task (i.e. takes a step) amounts to additional instances of inter-task 506 competition. Thus, one strategy to improve performance might be to ex- 507 ecute the walking task less often under dual-task load by increasing 508 stride length. Similar results have been reported previously (Li et al., 509 2012; Lovden et al., 2008) and considered adaptive to reduce inter- 510 task competition. In addition, one could make every effort to be out- 511 of-synch with the competing task. Considering that the average inter- 512 stimulus interval was 900 ms, a 44-ms increase in stride time from 513 1165 to 1209 ms might be suggestive of an effort to reduce CMI through 514 increased de-synchronization of tasks. A far more consistent pattern of 515 results can be found in studies with older individuals, where it is com- 516 monly reported that there is a reduction in walking speed and cognitive 517 performance under dual-task load (for a review see Al-Yahya et al., 518 2011). Again, the fact that age-related studies show a far more 519



Fig. 6. a) Statistical cluster plots (top row) assessing onset and distribution of differential ERP responses between sitting versus the two walking conditions (deliberately & briskly) and between walking deliberately versus walking briskly. Color values indicate the result of point-wise t-tests evaluating the differential activation across the 900 ms time epoch (x-axis) and 64 electrode montage (y-axis; see Methods for details of electrode locations). For clarity, only p values <0.05 are color-coded, and only then when fifteen consecutive data points (30 ms) exceeded this criterion. b) TANOVA (bottom row) assessing periods of statistically significant topographical differences between conditions.

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Fig. 7. Topographical distribution of voltage activity across the scalp depicting maps at 400, 425, 450, 475, 500, 525, and 550 ms. The interval from 400 to 550 ms was chosen based on the TANOVA results, which indicate significant differences of topographical distribution between sitting and walking conditions during this time period. Scalp maps spanning the P300 timeframe reveal a shift towards a more anterior distribution as participants perform the task while walking.

consistent pattern with costs commonly seen in the elderly speaks to
 the well-documented notion of higher processing resources in young
 walkers and their ability to adapt to dual-task load.

The absence of cognitive dual-task costs (even at increased walking 523 speed) might indicate that walking is largely governed by automatic 524sub-cortical and spinal-based processes and no or minimal cognitive-525motor interference (CMI) is therefore introduced. However, a growing 526number of electrophysiological and neuroimaging studies have pro-527528duced evidence for cortical involvement in human locomotion (Gwin et al., 2011; Harada et al., 2009; Suzuki et al., 2008). Alternatively, 529cognitive-motor interference occurred, but the load introduced by 530531walking was not sufficient to compromise inhibitory task performance. The present ERP results, however, clearly indicate differences in neural 532533processing associated with inhibition between sitting and walking. The results also indicate that dual-task load targets specific processing 534stages of the inhibition task. That is, we found no VEP differences be-535tween sitting and walking, which indicates that sensory-perceptual pro-536cessing stages of the inhibitory task are not affected by walking load. 537538The most robust dual-task effects in terms of amplitude reduction 539were found for the N2, which was evident across all three midline electrode sites. No differences in N2 peak latency were observed under 540dual-task load. For the P3, amplitude reductions were seen only over 541centro-parietal scalp regions. Furthermore, the P3 peak latency was 542543shortened by about 38 ms under dual-task load, indicating that the initiation of P3-related processing occurs earlier while walking. Finally, P3 544scalp maps showed a shift from a parietal to a more central maximal dis-545tribution between single and dual-task load. Topographical analysis of 546the ERP revealed dissimilarity of scalp distributions between sitting 547and walking during a time period from ~475 to 550 ms. In summary, 548we found robust differences in amplitude, latency and scalp distribution 549of the ERP components associated with inhibitory functioning between 550sitting and walking, suggesting alteration of neuro-cognitive processing 551 552under increased task load.

There are numerous studies using the P300 amplitude as a measure 553 of inter-task competition for processing resources (for a review see Kok, 554 2001). In a series of studies by Wickens and colleagues, the difficulty of 555 tracking a visual stimulus using a control stick tracking device was ma- 556 nipulated in a 'primary' task, while participants were also required to 557 detect infrequent auditory stimuli in a secondary oddball task (Isreal 558 et al., 1980a,b; Kramer et al., 1983; Wickens et al., 1977). The underlying 559 assumption was that by increasing the difficulty of the primary task one 560 could use the P300 amplitude as a probe to measure the decrease in re- 561 sources available to the secondary task. Reaction time for auditory odd- 562 ball detection increased with increasing primary task load, indicating 563 that task difficulty was indeed effectively manipulated. The effects of 564 primary task load on the 'secondary' P3, however, yielded rather 565 mixed results. In one of these studies, primary task was manipulated 566 by varying the velocity and frequency of directional reversals of the visu- 567 al stimulus making it increasingly difficult to (manually) track the stim- 568 ulus (Isreal et al., 1980a). The auditory P3 amplitude decreased in the 569 dual-task relative to single task conditions, but no further reduction of 570 P3 amplitude was observed for increasing levels of difficulty in the con- 571 trol of the tracking device in the primary task. Results showing dual-task 572 P3 reduction without further reduction by primary task load are difficult 573 to reconcile with the notion that both tasks rely on common processes of 574 limited capacity. In contrast, the same authors found that P3 amplitude 575 to the auditory oddball was sensitive to the primary task difficulty, 576 showing a further reduction for monitoring eight relative to four visually 577 displayed elements in the primary task (Isreal et al., 1980b). Based on 578 these and other results (Kramer et al., 1983, 1987), Wickens and col- 579 leagues suggested that P3 amplitude is mainly sensitive to manipula- 580 tions that tax perceptual and/or central processing as opposed to 581 motor processing. Here, we found that walking led to a reduction of 582 the P3 amplitude on NoGo trials, but no further reduction was observed 583 when load was increased (i.e. between deliberate and brisk walking 584 speeds). And compellingly, there were no concomitant increases in 585

behavioral costs in terms of reaction times to the Go stimuli or in the
rates of commission errors to the NoGo stimuli as a function of walking
speed, casting further doubt on the notion that P300 amplitude reduction under dual-task load reflects inter-task competition for limited processing resources.

A potentially more nuanced view emerges when one considers the 591fact that in addition to reduced P3 amplitude, we also observed a sub-592stantially different topographical distribution of the P3 here during the 593594dual-task conditions relative to the single-task condition. That is, rather 595than a modulation of the same processing resources, the current results 596suggest that the processing strategy itself has been changed. That the P3 distribution we observe is more anterior during the dual-task walking 597conditions also suggests that additional prefrontal resources have 598599been brought to bear and that perhaps a more cognitively demanding strategy has been engaged. Indeed, the fact that the earlier N2 is so 600 greatly attenuated during the walking conditions and that the P3 is 601 also found to peak earlier, also points to a significant change in process-602 ing strategy. We would propose that this pattern of effects, induced by 603 the shift from single-task to dual-task performance, likely reflects a 604 shift from a relatively automatic and early processing mode, as reflected 605 by the strong induction of the N2, to a more cognitively effortful and 606 somewhat later processing strategy that is reflected by engagement of 607 608 more anterior frontal control regions during the P3 timeframe. It is of some interest in this context that more frontally distributed P300 re-609 sponses with advanced age have been consistently reported in the 610 aging literature (Anderer et al., 1996; Fabiani and Friedman, 1995; 611 Friedman and Simpson, 1994; Friedman et al., 1993), with studies sug-612 613 gesting P300 anteriorization as a mechanism to engage additional resources to compensate for age-related decline, an account that accords 614 well with our notion here of additional engagement of anterior regions 615 616 under more effortful conditions.

The MOBI approach facilitates the integrated analysis of electro-617 618 cortical signals with precise measures of gait parameters while participants engage in demanding attentional tasks during active movement, 619 providing a considerably more realistic assessment of performance 620 under natural environmentally taxing situations. Evidence linking 621 brain cortical markers to gait pattern and to failed adaption to multiple 622 623 challenges, something we encounter constantly in our daily life, will greatly enhance our knowledge about cortical contributions to mobility 624 issues in older adults. Results indicating a shift from automatic to more 625 controlled processing of motor behavior in advanced age (Heuninckx 626 627 et al., 2005, 2010) would suggest that older individuals are further limited in adapting processing resources across dual-tasks. Assessing corti-628 cal flexibility in the face of these challenges allows us to identify 629 individuals who fail to redeploy neural resources appropriately. Relating 630 this inflexibility to fall risk will potentially lead to objective neural bio-631 632 markers of fall risk that can increase and accelerate our predictive 633 capacity.

634 Study limitations

635 Clearly, one of the express purposes of a study such as the current 636 one is to move towards more naturalistic environmental conditions and to begin to assay human neural functioning while participants are 637 actively exploring and physically engaged with their surroundings. 638 Even so, it is evidently the case that walking on a treadmill, while 639 640 going some way towards this goal, necessarily constrains the gait pattern, since the speed of walking is deterministic. Simply put, partici-641 pants do not have the option of slowing down under dual-task situa-642 tions. This is a clear limitation of our study, and a move to the use of 643 portable, wearable high-density EEG systems will likely provide ever 644 more realistic setups (Casson et al., 2008). Needless to say, as the partic-645 ipant begins to move more freely in the environment, the delivery of a 646 tightly timed cognitive task becomes considerably more challenging, 647 so there are inherent compromises to each new advance in the ability 648 649 to record from moving humans. Despite the constraint of constant walking speed imposed by the treadmill, prior work using this method 650 has shown robust dual-task costs on gait, including changes in step-651 width variability (Grabiner and Troy, 2005), cadence (Simoni et al., 652 2013), and gait variability (Li et al., 2012; Szturm et al., 2013). Thus, 653 while slowing down may not be an option, it is clearly the case that 654 meaningful adjustments of motoric behavior can be assayed. As such, 655 this preparation does provide the opportunity to meaningfully assess 656 the interplay between cognitive control systems and sensory-motor in-657 tegration, albeit under not entirely naturalistic circumstances. 658

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